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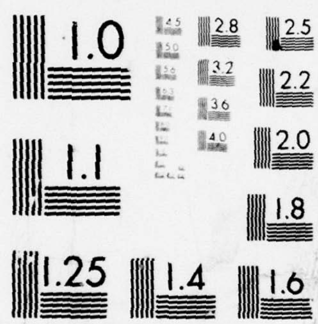

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A Proposed Resolution of Curious Conflicts in the Literature on Linear Syllogisms

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Students of reasoning have engaged in a vigorous debate regarding the representations and processes used by subjects solving linear syllogisms. Meaningful communication between proponents of the various positions has been hampered by the appearance of curious conflicts in reported data sets for the linear syllogism problems. The present experiment was intended to isolate the source of these conflicts in the literature. Eighteen adult subjects received linear syllogisms under instructions designed to yield

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speeds commensurate with error rates of about 10%. Latency and error data were analyzed both separately (via multiple regression) and jointly (via canonical regression). These data were also analyzed via pseudo-deadlines, according to which responses were counted as correct if they were correct and fell below a given pseudo-deadline, and were counted as erroneous if they were incorrect or fell above a given pseudo-deadline. The analyses revealed that the source of the conflicts in the literature is the failure of researchers to appreciate the complex interrelationships between latency and error rate. When these interrelationships are taken into account, the conflicts disappear.

A Proposed Resolution of Curious Conflicts

in the Literature on Linear Syllogisms

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Abstract

Students of reasoning have engaged in a vigorous debate regarding the representations and processes used by subjects solving linear syllogisms. Meaningful communication between proponents of the various positions has been hampered by the appearance of curious conflicts in reported data sets for the linear syllogism problems. The present experiment was intended to isolate the source of these conflicts in the literature. Eighteen adult subjects received linear syllogisms under instructions designed to yield speeds commensurate with error rates of about 10%. Latency and error data were analyzed both separately (via multiple regression) and jointly (via canonical regression). These data were also analyzed via pseudo-deadlines, according to which responses were counted as correct if they were correct and fell below a given pseudo-deadline, and were counted as erroneous if they were incorrect or fell above a given pseudo-deadline. The analyses revealed that the source of the conflicts in the literature is the failure of researchers to appreciate the complex interrelationships between latency and error rate. When these interrelationships are taken into account, the conflicts disappear.

A Proposed Resolution of Curious Conflicts
in the Literature on Linear Syllogisms

In a linear syllogism, an individual is presented with two premises, each describing a relation between two terms. One of the terms overlaps between premises. The individual's task is to use this overlap to infer the relations among the three terms of the linear syllogism, and then to answer a question about one or more of these relations. A typical linear syllogism is

Jon is taller than Bob.
Sam is shorter than Bob.
Who is tallest?

Psychologists have been investigating the representations and processes people use in solving linear syllogisms since Burt's (1919) adoption of the problem for one of his tests of mental ability. In recent years, a vigorous debate has arisen regarding whether subjects' representations of the relations among terms are spatial (DeSoto, London, & Handel, 1965; Huttenlocher, 1968; Huttenlocher & Higgins, 1971), linguistic (Clark, 1969a; Clark, 1969b), or a mixture of both (Sternberg, Note 1). Data recently collected from four experiments in my laboratory make a strong case for a proposed mixture model (Sternberg, Note 1). These data fail to resolve the debate, however, because of surprising inconsistencies across data sets collected in different laboratories. In particular, whereas my own data and those of Potts and Scholz (1975) and of Hunter (1957) support the mixed model, data collected by Clark (1969a, 1969b) and by Keating and Caramazza (1975) support a linguistic model (see Sternberg, Note 1).

The present paper seeks to resolve these inconsistencies, and in so doing, to advance our understanding of how linear syllogisms are solved. In the next section of the paper, the three alternative models of linear syllogistic reasoning are briefly described. (A more detailed description of each model can be found in Sternberg, Note 1.) Then possible sources of conflict in data testing these models are described. Finally, an experiment is presented that seeks to resolve the conflicts regarding which model is best. The results of the experiment may be of interest to experimental psychologists engaged in modeling thought processes in tasks other than linear syllogisms, since the results call into question our often cavalier ways of dealing (or failing to deal) with the relationships between response time and error rate.

MODELS OF LINEAR SYLLOGISTIC REASONING

In this section of the paper, three alternative models of linear syllogistic reasoning--a spatial model (based upon the accounts of DeSoto et al., 1965; Huttenlocher, 1968; and Huttenlocher & Higgins, 1971), a linguistic model (based upon the account of Clark, 1969b), and a mixed model (based upon the account of Sternberg, Note 1)--will be described briefly and compared. An example of a linear syllogism, "<u>C</u> is not as tall as <u>B</u>; <u>A</u> is not as short as <u>B</u>; Who is shortest?" will be used to facilitate comparison.

<u>Spatial Model</u>

In the proposed spatial model, the terms of the syllogism are arranged into an imaginal, linear spatial array that is an analogue of a physical, linear array. Thus, the terms of the example problem will be arranged into an imagined array in which <u>A</u> is at the top, <u>B</u> is in the middle, and <u>C</u> is at the bottom.

The subject must first read the terms of the problem. The terms in each premise are first arranged in a two-item array. The initial arrangement

disregards the negation, if one is present. Thus, the first pair of terms is arranged as $\begin{matrix}C\\B\end{matrix}$ and the second pair as $\begin{matrix}B\\A\end{matrix}$. Arrangement of terms from the top down (as is done when the adjective _tall_ or _taller_ appears in the premise) is easier and hence faster than arrangement of terms from the bottom up (as is done when the adjective _short_ or _shorter_ appears in the premise). Next, if a negation appears in a premise, a new array is constructed in which the terms of the old array are flipped around in space. In the example, two new arrays, $\begin{matrix}B\\C\end{matrix}$ and $\begin{matrix}A\\B\end{matrix}$, are constructed.

The subject next attempts to integrate the two arrays. This integration will be easier if the subject worked from the ends of the larger array inward rather than from the middle outward in constructing the two smaller arrays. A possible reason for this directional effect is that working from the ends inward brings one to the pivot, or middle term of the series. If one ends up on the middle term, then it is immediately available for use as the pivot of the larger array. If one does not end up on the middle term, one must search for it, taking additional time. In an affirmative problem, this means that the preferred order of terms in a premise is the outermost term followed by the middle term. In a negative equative problem (such as the example problem), the preferred order is reversed, since the flipping of terms reverses the last term to be encoded in working memory.

Just as it was easier to work from the top down within each of the two two-item arrays, it is easier to work from the top down across the two two-item arrays, so that processing is facilitated if the first premise consists of the _A_ and _B_ (top two) terms of the array, rather than the _C_ and _B_ terms, as in the example. The subject integrates the two arrays into a single array, $\begin{matrix}A\\B\\C\end{matrix}$, reads the question, and then seeks the answer to the question in the array. In the example, the correct answer is _C_.

Linguistic Model

In the proposed linguistic model, the terms of the syllogism are stored by way of functional relations that represent the relation between them at the level of linguistic deep structure: (B is tall+; C is tall); (B is short+; A is short). In the linguistic model, unlike in the spatial model, information from the two premises is left unintegrated.

The subject begins solution by encoding the surface structural strings into linguistic deep structures of the kind shown above. Marked adjectives (such as short and shorter) are assumed to be stored in more complex form than unmarked adjectives (such as tall and taller), and hence are assumed to take longer to encode. The initial encoding disregards the negation, if one is present. Thus, the first pair of terms is arranged as (C is tall+; B is tall) and (A is short+; B is short). Upon encountering the negations, the subject effects a linguistic transformation that brings the propositional strings to the form shown in the preceding paragraph.

It is assumed in this model that in order to conserve space in working memory, the encoding of the first premise is compressed, so that only the first relation, in the example, (B is tall+), remains in working memory. Since B is the middle term, the pivot of the three-item relation is retained in working memory, and locating it does not present a problem. But if the first premise had been "B is not as short as C," only (C is short+) would have been retained in working memory, resulting in the subject's needing to search long-term memory for the missing pivot term (B). This search for the pivot consumes additional time.

Having found the pivot, the subjects reads the question. If the question contains a marked adjective, additional time is spent encoding it. In the example, the subject seeks the individual who is shortest. All propositional

information is now made available for the final search. Solving the problem requires finding the individual who is short+ relative to the pivot, but no such individual is found in the example. The reason no such individual is found is that the form of the question is incongruent with the way in which the answer term has been encoded. Whereas the shortest term, C, was previously encoded as tall (relative to the tall+ B), the question asks for the person who is shortest. The subject must therefore make the question congruent with the problem terms as encoded. He or she does so by looking for the least tall individual—someone is tall- relative to a tall pivot, or tall relative to a tall+ pivot. The subject can now respond with the correct answer, C.

Linguistic-Spatial Mixed Model

In the proposed mixed model, the terms of the syllogism are first decoded into linguistic deep-structural propositions (as in the linguistic model), and are then encoded into spatial arrays (as in the spatial model). However, the mixed model involves only a subset of the processes used in the spatial and linguistic models, and adds some processes appearing in neither of the other two models.

The subject begins solution by decoding the surface-structural strings into linguistic deep structures. These linguistic deep structures then form the basis for the construction of spatial arrays, one for each premise. Marked adjectives are assumed to increase processing time, both through increased linguistic decoding time and through increased spatial encoding time. Negations are handled as in the spatial model, with new arrays constructed from the original arrays by flipping the elements of the original arrays in space.

In order for the subject to combine the terms of the premises into a single spatial array, the subject needs the pivot available. The pivot is

either immediately available from the spatial encoding of the premises, or else it must be located. The pivot is immediately available in all (a) affirmative problems and (b) negative equative problems in which the second premise begins with the pivot (see Sternberg, Note 1, for a description of the mechanism of pivot search). In the example problem, the second negative equative premise does not begin with the pivot, but with an end term, so that the pivot must be located as the term that overlaps between the two two-item spatial arrays. Once the pivot has been located, the subject seriates the terms from the two two-item spatial arrays into a single three-item spatial array. In forming the array, the subject starts with the terms of the first premise, and ends with those of the second premise. The subject's mental location after seriation, therefore, is in that half of the array described by the second premise (which is the top half in the example). The subject next reads the question. If there is a marked adjective in the question, the subject will take longer to decode the adjective linguistically, and to seek the response to the problem at the nonpreferred (usually bottom) end of the array. The response may or may not be immediately available. If the correct answer is in the half of the array where the subject just completed seriation (his or her active location in the array), then the response will be immediately available. If the question requires an answer from the other half of the array, however, the subject will have to search for the response, mentally traversing the array from one half to the other and thereby consuming additional time. In the example, the subject ends up in the top half of the array, but is asked a question about the bottom half of the array ("Who is shortest?"), requiring search for the response.

Under certain circumstances (see Sternberg, Note 1), the subject checks the linguistic form of the proposed response against the form of the adjective

in the question. If the two forms are congruent, the subject responds with the designated answer. If not, the subject first makes sure that congruence can be established, and then responds. In the example, congruence must be established, since the shortest term, C, has previously been decoded in terms of the adjective tall. Once congruence has been established, C can be recognized as the correct answer to the example problem.

Summary

The models all agree that some form of encoding, negation, marking, and response contribute to response latency, and although the models in some cases disagree as to the exact form each operation takes, mathematical parameters corresponding to the durations of these operations are estimated from the same independent variables for each model. Each model also contains a pivot search operation, although the parameter corresponding to the duration of this operation is estimated in a different way for each model. The spatial model further contains a premise order parameter, and the mixed model further contains a response search parameter. The linguistic model further contains a noncongruence parameter, which appears only under special circumstances in the mixed model (including the circumstances of the experiment to be described in this report).

CONFLICTS IN DATA SETS TESTING THE MODELS

The data from previous research reveal curious conflicts. Except for the data set of Clark (1969b),[1] the data sets appear to be reliable, and so the inconsistencies among data sets seem likely to be due to factors other than chance. What factor or factors might be responsible for the inconsistencies? Two possibilities are considered in this article. First, there may be a difference in speed-accuracy tradeoff between subjects in the experiments supporting the mixed model and subjects in the experiments supporting the linguistic model.

The error rate in each of the Sternberg (Note 1) experiments was 1%; in the Potts and Scholz (1975) experiment (Experiment 1, Group 1), the error rate was 7%; Hunter (1957) did not report error rates. The error rate in the Clark (1969b) experiment was 7%; it was 30% in the Clark (1969a) experiment, and 22% in the Keating and Caramazza (1975) experiment. These last two experiments used a procedure different from that of the other experiments, where standard latency measurements for solving individual items were taken. In these two experiments, subjects were given 10 seconds to solve each problem. An error was counted if the subject either responded incorrectly or failed to respond at all in the 10 seconds. The deadline procedure used by Clark (1969a) and by Keating and Caramazza (1975) would seem to encourage subjects to emphasize speed at the expense of accuracy, since any response taking longer than 10 seconds, whether right or wrong, was counted as an error. Support in these experiments for the linguistic model may thus have been due to the higher error rates obtained. Second, the procedure used in these two experiments may itself have been responsible for the conflicts in the data. If we ignore the probably unreliable data of Clark (1969b), we find that data obtained under standard response-time procedures tend to support the mixed model, whereas data obtained under the deadline procedure tend to support the linguistic model. If experimental procedure is the factor responsible for the difference in model fits, then two subfactors need to be distinguished. First, the use of a deadline may in and of itself lead to a linguistic strategy. Second, the modeling of errors (in the deadline procedure) rather than latencies (in the standard procedure) may lead to the apparent superiority of the linguistic model. The research to be described was intended to distinguish among these possible explanations of the conflicts among data sets.

EXPERIMENT

A single experiment proved sufficient to distinguish among the hypotheses considered above regarding the conflicts among data sets, and to discover the responsible factor. In this experiment, subjects solved linear syllogisms under the standard conditions, with as long as they needed to solve each item. However, subjects were strongly encouraged to solve items as rapidly as they could, and a bonus was paid to reward fast performance accompanied by only a moderate degree of accuracy.

Method

Subjects

Subjects were 18 undergraduates attending the Yale summer term. Of these subjects, 10 were women and 8 were men.

Materials

Stimuli were two-term series problems and three-term series problems (linear syllogisms). The 32 types of three-term series problems varied dichotomously along five dimensions: (a) whether the first premise adjective was marked or unmarked; (b) whether the second premise adjective was marked or unmarked; (c) whether the question adjective was marked or unmarked; (d) whether the premises were affirmative or negative; (e) whether the correct answer was in the first or second premise. The 8 types of two-term series problems varied dichotomously along three dimensions: (a) whether the premise adjective was marked or unmarked; (b) whether the question adjective was marked or unmarked; (c) whether the premise was affirmative or negative. There were three replications of each item type, one using the adjective pair taller-shorter, one using the adjective pair better-worse, and one using the adjective pair faster-slower.

Apparatus

Two- and three-term series problems were administered via a Gerbrands two-

field tachistoscope with an attached centisecond clock.

Design

The design of the experiment was completely within-subject: Each subject received each item type three times, once with each adjective. The dependent measures of interest were response time and error rate.

Procedure

Subjects were first shown examples of typical two- and three-term series problems, and were told that their task was to solve items of these types. These items, and the practice items given later, used the adjective pair older-younger, which was not used in the actual test items. Instructions to subjects indicated that the subjects should solve problems at a rate that would allow about 10% errors, and that a monetary bonus would be paid for fast performance at an error rate of about 10%. In fact, the bonus was computed strictly on the basis of error rate. A bonus of 50¢ was paid for four errors (out of 40 items), 35¢ for three or five errors, 15¢ for two or six errors, 10¢ for one or seven errors, and 0¢ for zero or eight or more errors. Subjects were told after each third of the items was completed what their bonus for the preceding 40 items was, and what their maximum bonus could have been (50¢). Subjects were then told to speed up if their error rate was under 10%, or to slow down if their error rate was over 10%.

All testing was done in one session. Testing began with the administration of eight practice items. Next, subjects received 120 stimulus items. Items were blocked by number of terms (two or three) and by adjective pair (taller-shorter, better-worse, faster-slower), with order of blocks counterbalanced across subjects.

Results

The results of the experiment will be presented in four parts. In the first, the success of the speed-accuracy tradeoff manipulation will be evaluated. In the second, comparability of the present data set to previous ones, as measured by standard data-analytic techniques, will be assessed. In the third, latency and error data will be analyzed as though various deadlines had been used in presenting the stimulus items. The data will be partitioned on the bases of pseudo-deadlines of 2, 4, 6, 8, 10, 12, 14, 16, and ∞ seconds. In the fourth, the latency and error data will be considered simultaneously as joint dependent variables. This analysis will show the serious consequences of failing to take into account both solution latency and error rate, as well as the relationships between them.

Success of the Speed-Accuracy Tradeoff Manipulation

The first issue that needs to be addressed is whether the speed-accuracy tradeoff manipulation in the instructions to subjects was successful. The mean solution latency for the three-term series problems in this experiment was 5922 $\pm$ 128 msec. Respective means for Experiments 1-4 of Sternberg (Note 1) were 7285 $\pm$ 177 msec, 7489 $\pm$ 188 msec, 7002 $\pm$ 170 msec, and 7069 $\pm$ 161 msec. The mean response time in the present experiment was therefore more than one second faster than the mean response time in any of the earlier experiments, indicating that the instructions in the present experiment were successful in speeding subjects up. The mean error rate in the present experiment was 7%, compared to 1% in each of the earlier experiments, indicating that the instructions were also successful in increasing error rates. The speed-accuracy tradeoff manipulation may therefore be viewed as having succeeded.

Comparability of Present Data to Previous Data

Intercorrelations of data sets. The present data set is highly similar

to those presented in Sternberg (Note 1). The median intercorrelation across data sets from the four experiments presented in Sternberg (Note 1) was .84, whereas the median intercorrelation between the present data set and these four previous data sets was .86. Since the split-halves reliability of the present data set was also .86,[2] and since the previous data had a median split-halves reliability of .89, the correlations between the present and previous data sets were about as high as the reliabilities of the data would allow.

Qualitative fits of the models to the latency data. Five-way analyses of variance were conducted on the observed solution latencies and on the predicted solution latencies for each model. The five factors in the analyses were the same ones that generated the $2^5 = 32$ linear syllogism types in the experiment (see *Materials* section). Each cell of the 2^5 design contained three observations, namely, the means over subjects of the solution latencies for a given adjective pair.

The results of the analyses of variance replicated those of Sternberg (Note 1). The major findings were these:

1. The effect of marked adjectives was highly significant for both premises, $F(1,64) = 47.95$, $p<.001$ for premise 1 and $F(1,64) = 7.83$, $p<.01$ for premise 2, but only marginally significant for the question, $F(1,64) = 3.63$, $p<.10$. All three models predicted a marking effect of 35 csec for both premises and question, although the observed effects were 63, 25, and 17 csec respectively. The models were therefore successful in predicting an effect, but unsuccessful in predicting the differential effect of where the marked adjective occurred.

2. The observed effect of negation, 65 csec for the two premises combined, was highly significant, $F(1,64) = 50.75$, $p<.001$, and equal in magnitude to the effect predicted by each of the three models.

3. Items with the correct answer in the first premise were significantly

harder than items with the correct answer in the second premise, $F(1,64) = 28.28$, $p < .001$. The mixed model correctly predicted this effect and its duration, 49 csec. This latency reflects the need of the subject to search for the response in items where the response is not immediately available. The linguistic and spatial models, lacking a response search operation, failed to predict this effect.

4. The observed data showed five statistically significant interactions. The mixed model correctly predicted four, the linguistic model, three, and the spatial model, two of these interactions. The mixed and spatial models each predicted one spurious interaction; the linguistic model predicted two.

Quantitative fits of the models to the latency data. Each of the three models was fit separately to group latency data for three-term series problems only, for two- and three-term series problems together, and for three-term series problems for each adjective considered separately. Table 1 shows the means and standard errors of the latency data, plus the values of R^2 obtained in predicting the latency data from the independent variables specified by each of the three models (and described in detail in Sternberg, Note 1). The higher values of R^2 for the two- and three-term series problems in combination are due to the separation of the encoding component in these analyses; this component is confounded with the response component in the analyses of three-term series problems only. In general, the results closely replicate those of Sternberg (Note 1), except for the faster latencies obtained due to the speed-accuracy tradeoff manipulation.

Insert Table 1 about here

The mixed model performed considerably better than did either the linguistic or spatial model: The value of R^2 for the mixed model was .251 higher than that for the linguistic model, and .237 higher than that for the spatial model.

Even with the optional noncongruence parameter deleted, R^2 for the mixed model, .761, was still .155 better than that for the next best model. Deletion of this parameter is of doubtful theoretical justification, however, since the mixed model specifies that the full set of parameters is necessary to account for subjects' performance under these circumstances (see Sternberg, Note 1). Each subject's data was also analyzed individually, and the results of the individual model fitting also supported the mixed model. Although the mixed model is superior to the alternative models, it is not the true model: The residual variance was highly significant ($p<.001$), indicating that systematic variance was still left unaccounted for.[3]

Although the present data set is highly correlated with the preceding (Sternberg, Note 1) data sets, leading to comparable patterns of model fits, there was a large difference between mean latencies in the present versus the preceding tasks. By decomposing response time into components, and then comparing latency parameter estimates across data sets, it is possible to localize the effect of the speed-accuracy tradeoff manipulation upon information processing. Table 2 presents parameter estimates from the present experiment and two previous experiments (from Sternberg, Note 1) that were highly comparable to the present experiment except for the emphasis upon accuracy in the instructions. A com-

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Insert Table 2 about here

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parison of the parameter estimates for the various experiments shows a general decrease in the latencies of the various component processes under the speed condition. But the decrease is not uniform: It is due primarily to more rapid encoding, that is, construction of the spatial array showing the relationships among terms of the problem. Rapid construction of this array would seem likely to increase subjects' susceptibility to errors, and indeed, a decrease in overall latency of one second was bought at the cost of a seven-fold increase in error rate.

So far, the data have not revealed why the linguistic model performs better than the mixed model under certain circumstances. They have shown, however, that the difference in model performance cannot be attributed merely to a difference between speed-accuracy tradeoff conditions in the various experiments. The first suggested explanation of the conflict among data sets in the literature on linear syllogisms is therefore shown to be incorrect.

Reanalysis of Data with Pseudo-Deadlines

The second suggested explanation of the conflict in the literature was based upon the use of a deadline procedure in the reliable data sets supporting the linguistic model, but of a standard unlimited-time procedure in the reliable data sets supporting the mixed model: The difference in relative model fits might be due to a difference in procedures. Ideally, one would want to test this hypothesis by testing multiple groups of subjects under various deadlines. The limiting case of these deadlines would be infinite time, which would be equivalent to the standard unlimited-time procedure. An experiment with a large number of different deadlines is impractical, however. An exploratory procedure was therefore used in which the data were partitioned by means of pseudo-deadlines. In this procedure, the data were reanalyzed as if each of a sequence of increasing deadlines had been used. As a first pseudo-deadline, all correct responses with latencies of two seconds or less were counted as "corrects;" all error responses and responses with latencies of over two seconds were counted as "errors." The pseduo-deadline procedure was then repeated for simulated deadlines of 4, 6, 8, 10, 12, 14, 16, and ∞ seconds. In this last case, only genuine error responses were treated as errors, since, of course, all latencies were finite.

Error rates. Means and standard errors of the proportions of errors, as well as fits of the models to proportions of errors, are shown in Table 3. Modeling of logarithms of numbers of correct responses yielded comparable results.

Keep in mind that in the present method of analysis, each subject receives a score of 0 (correct) or 1 (error) on a given item; the data become approximately continuous only when averaged across subjects.

Insert Table 3 about here

The data reveal a most interesting pattern: For pseudo-deadlines of under 10 seconds, the performance of the mixed model is clearly superior to the performance of any of the other models. At 10 seconds, however, the relative performances of the models change dramatically. Although the predictive power of all the models is reduced, the predictive power of the mixed model is reduced to a far greater extent than that of either of the other two models. The linguistic model now becomes slightly superior to the mixed model, and this superiority holds up at 14, 16, and ∞ seconds (where only genuine error responses are modeled). Thus, a cutoff of 10 seconds, that which happened to have been used by Clark (1969a) and by Keating and Caramazza (1975), turns out to be a crossing point in the relative performances of the mixed and linguistic models. At this cutoff, there is a sharp decrease in the variance of error rates across items (as can be inferred from the large drop in standard error as shown in the table), and only 13% of the responses are being counted as errors. It therefore appears that the interpretation and modeling of error rates from the deadline (or pseudo-deadline) procedure is somehow responsible for the crossover in relative model fits, although the mechanism behind the crossover remains to be explained.

Some understanding of why the crossover happens can be gleaned by examining the standardized regression coefficients (beta weights) for each of the parameters of each model at the various pseudo-deadlines. These coefficients are shown in Table 4. In order to provide a baseline for comparison, standardized regression coefficients are also shown for response times as modeled in the preceding section of this article.

Insert Table 4 about here

Consider first the standardized coefficients for the mixed model. All coefficients were statistically significant in predicting response times, but not in predicting error rates as analyzed under the pseudo-deadline procedure. In particular, the coefficients for pivot search and response search, the two parameters unique to the mixed model, were statistically significant up to 8 seconds, but were nonsignificant thereafter (except for pivot search at 12 seconds). The standardized coefficient for noncongruence also started off significant and became nonsignificant, although not until a pseudo-deadline of 16 seconds. The steep decrease in R^2 for the mixed model at 10 seconds can thus be understood in terms of the failure of pivot search and response search to distinguish between "correct" and "error" responses at this and subsequent pseudo-deadlines.

Consider next the standardized coefficients for the linguistic model. Of greatest interest was the pattern of coefficients for linguistic pivot search. This parameter did not contribute significantly to prediction of response time, but it did contribute significantly to prediction of error rates from the 6 second cutoff to the cutoff of ∞ seconds. This pattern of significant prediction of error rate coupled with nonsignificant prediction of response time is most unusual, since response time is often viewed as a more sensitive measure of the same thing measured by error rate. Discussion of this unusual finding will be deferred until later. The pattern of loadings indicates that the drop in predictive power of the linguistic model at 10 seconds is attributable to only a single parameter, negation, as opposed to two parameters, pivot search and response search, in the mixed model. It is therefore not surprising that the drop for the linguistic model was smaller than that for the mixed model.

Finally, consider the standardized coefficients for the spatial model. An examination of these coefficients reveals that the drop in predictive power at 10 seconds is due to the reduction in predictive power of the negation parameter, as in the linguistic model.

To summarize, the analyses of error rates modeled under the pseudo-deadline procedure show that the linguistic model becomes superior to the mixed model in predictive power when the variance across items in error rates becomes very small. In the present data (and very likely in previous data as well), a sharp decrease in variance occurs at a pseudo-deadline of 10 seconds. At this point, only 13% of responses are counted as errors. Both the mixed and linguistic models show decreases in predictive power at the 10 second cutoff, but the decrease is much more pronounced for the mixed model than for the linguistic model. This is because two parameters in the mixed model—pivot search and response search—become useless in predicting errors at this point. In the linguistic model, only negation loses its predictive power at this point.

Response times. The analyses presented above suggest that something about the deadline or pseudo-deadline procedures leads to conclusions different from those drawn when standard unlimited-time procedures are used. It is not clear yet, however, what this "something" is. As noted earlier, it may be the deadline or pseudo-deadline procedures themselves; or it may be the modeling of error data, irrespective of the use or nonuse of deadlines or pseudo-deadlines. Note in this regard that modeling of error rates in the limiting pseudo-deadline condition (∞ seconds) results in superior prediction for the linguistic model over the mixed model. In order to distinguish between these two possibilities, each of the three models was fit to latency data analyzed via pseudo-deadlines. In one set of analyses, the models were fit to latencies above each of the pseudo-deadlines. Latencies below the cutoffs were treated as missing data. In a

second set of analyses, the models were fit to latencies below each of the pseudo-deadlines. Latencies above the cutoffs were treated as missing data. If the mere use of pseudo-deadlines (or deadlines) accounts for the conflicts in the data, then the mixed model should perform better than the linguistic model at some cutoffs but not at others. If, however, it is modeling of error data that is responsible for the conflicts, then the mixed model should be superior to the linguistic model, irrespective of the particular cutoff used.

Means, standard errors, and model fits for latencies above and below the cutoffs are shown in Table 5. Note that not every item type had any observations above or below every possible pseudo-deadline. For example, only 13 of the 32 item types had any observations with latencies of greater than 14 seconds; no item types had any observations with latencies of less than 2 seconds. The in-

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Insert Table 5 about here

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terpretation of the data in Table 5 is unequivocal. For all pseudo-deadlines under or over which there was statistically significant prediction, the mixed model was clearly superior to either the linguistic or spatial model. Thus, it was not the use of deadlines per se that resulted in the superiority of the linguistic model: If latencies are modeled under the pseudo-deadline procedure, the mixed model is always better. Rather, it was the use of error rate as a basis for modeling that resulted in the conflict. The mixed model better predicts latencies; the linguistic model better predicts error rates. The probable reason for the crossover in performance of the models at the 10 second cutoff is that at this point, almost all of the countable errors were actual errors rather than long solution latencies.

Modeling of Latency and Error Data Simultaneously

Model fitting by canonical regression. The analyses described above suggest that complete understanding of linear syllogistic reasoning requires simultaneous consideration of both solution latency and error rate as dependent variables. This simultaneous analysis was done here by canonical regression (Cooley & Lohnes, 1971; Sternberg, 1977b; Tatsuoka, 1971). In the present use of canonical regression, solution latency and error rate were considered jointly as dependent variables, with the independent variables the same as in each of the models as previously described. Canonical weights (analogous to beta weights in regression) are derived by least squares for each dependent and independent variable to maximize the canonical correlation between the two sets of variables. As in factor analysis (but not in simple or multiple regression), it is possible to have more than one set of weights, with each subsequent set of weights orthogonal to all previous ones and describing different aspects of the relationship between dependent and independent variables.

Mixed, linguistic, and spatial canonical models. Table 6 shows the fits of the mixed, linguistic, and spatial canonical models to the latency and error data, as well as the standardized parameter estimates (canonical weights) for each of the dependent and independent variables.

Insert Table 6 about here

The first canonical variate was statistically significant for each model. The mixed model clearly gave the best account of the first canonical variate. Indeed, the value of canonical R^2 for the mixed model, .849, was only trivially higher than the value of multiple R^2 for the mixed model (for latencies considered alone), .843 (see Table 1). The increments in R^2 for the other models

were also trivially small. The standardized parameter estimates for the dependent variables on the first variate reveal that solution latency was the main contributor to the variate, and the standardized parameter estimates for the independent variables on the first variate closely resemble those of the independent variables in predicting solution latency alone (see Table 4). The first variate, therefore, seems very closely to resemble solution latency considered in isolation from error rate.

The second canonical variate was statistically significant only for the linguistic model. The weights for the dependent variables reveal that error rate makes a large contribution to this variate, and that the contribution of solution latency is negative. This negative weight suppresses the variance in solution latency that is correlated with error rate. This suppression is needed in order to make the second canonical variate orthogonal to the first. The second canonical variate, then, apparently represents that part of error rate that is orthogonal to solution latency. Linguistic pivot search, which is unique to the linguistic model, makes the strongest positive contribution toward the prediction of this variate.

Full canonical model. The results obtained so far suggest that the mixed model is best in predicting solution latencies (which are represented by the first canonical variate), and that the linguistic model is best in predicting error rates, and in particular, that portion of error rate that is uncorrelated with solution latency (which is represented by the second canonical variate). These results suggest that some combination of the mixed and linguistic models may give a superior account of solution latency and error rate considered jointly to that given by either model alone. In order to investigate this possibility, a fully exploratory analysis was conducted in which a full model was tested that included all parameters of the three models

previously considered. The results of fitting this full model are shown in Table 7.

Insert Table 7 about here

The value of canonical R^2 for the first variate, .858, is only trivially higher than that value of canonical R^2 for the first variate when the mixed model is fit alone, .849. Even combining the parameters of the three models, therefore, one can't do any better than the mixed model in predicting the latency-based first variate. The value of canonical R^2 for the second variate, .432, represents a noticeable increase over the value of .268 for the linguistic model alone. As in the linguistic model alone, however, the linguistic pivot search parameter appears to be the truly powerful predictor of performance, with spatial pivot search making a secondary contribution.

Experience with canonical regression has showed that the standardized parameter estimates are often less readily interpretable than the correlations of the original variables with canonical variate scores (see Sternberg, 1977b). These scores are computed for each observation simply by summing the product of each standardized independent or dependent variable times its corresponding standardized weight. Correlations between the canonical variate scores and the original variables are presented in Table 8.

Insert Table 8 about here

Solution latency is very highly correlated with both the dependent and independent variate scores. Error rate is also fairly highly correlated with scores on the first variate. This pattern of correlations is to be expected if error rate is a less precise measure than solution latency of whatever it is that solution latency measures. In one aspect, therefore, error rate is

an imperfect substitute for solution latency. But in another aspect, error rate measures something solution latency does not measure (as expressed in the second canonical variate). This pattern is not unique to linear syllogisms: It appears for analogies as well (Sternberg, 1977b).

Turning to the correlations for the independent variables, one can see that all of the independent variables of the mixed model are significantly correlated with both the dependent and independent variate scores, except in one instance, response search. Of all the parameters, only linguistic pivot search shows significant and substantial correlations with both the dependent and independent second variate scores. Thus, it is indeed this operation that is responsible for the superiority of the linguistic model in accounting for error rate.

Discussion

The significant correlation of the linguistic pivot search variable with error rate but not solution latency initially seems perplexing. How is it possible for a variable to contribute to error rate but not to solution latency? A plausible explanation (Schustack, Note 2) is that the linguistic pivot search operation is always executed, but it takes a constant amount of time across item types and hence does not appear as a separate latency parameter. Instead, its latency is absorbed into the global constant (used in the models of linear syllogistic reasoning to estimate response component time). By this explanation, subjects always compress the first premise of a linear syllogism, and later retrieve from long-term memory the term that was temporarily deleted from working memory. However, the linguistic pivot search operation leads to errors in solution only in cases where the term that is temporarily deleted in compression is also the pivot term. In these cases, an error in the operation will result in selection of an incorrect pivot, and hence an

error in solution. In cases where the temporarily deleted term is not the pivot, the value of this term doesn't lead to selection of an erroneous pivot, and hence doesn't lead to an error in solution.

Subjects are generally not aware of the pitfalls posed by structural variables that contribute differentially to error rate but uniformly to solution latency. Consider, for example, a variant of a problem that is a classic in puzzle books: A plane traveling from the United States to Canada crashes directly on the border between the two countries. In what country will the survivors be buried? Most people unfamiliar with the problem respond quickly with either "the United States," "Canada," or "either country." The printed solution, however, will usually be that "survivors aren't buried" (at least, not immediately)! Suppose, though, the problem had been stated in this way: A plane traveling from the United States to Canada crashed directly on the border between the two countries. In what country will the deceased be buried? Readers who are tripped up by the first version of the problem would generally encode this second version of the problem in the same way as they would encode the first version, responding in approximately the same amount of time. Yet, they would be far more likely to respond with an "acceptable" answer to the second version. Because the source of difficulty in the first version of the problem is not recognized as such, it does not contribute differentially to solution latency. The true nature of the problem is misapprehended. Such misapprehensions are common in ability-testing situations. Subjects who score relatively poorly may perceive themselves as scoring well because they solve problems that are different from and easier than the ones actually posed. In multiple-choice tests, distractors are presented that capitalize upon the subjects' misapprehensions of the problems. The subjects thus never become aware of

their misapprehensions.

The results of the present experiment show the importance of modeling both solution latencies and error rates jointly (Sternberg, 1977b) as well as separately (Sternberg, 1977a, 1977b). Pachella (1974) has shown that differential error rates across conditions can drastically affect interpretation of latency outcomes, and the present results seem to indicate that the appearance of curious conflicts in the literature can arise simply from the failure to consider solution latency and error rate as conveying overlapping but by no means identical information. The conflict resided not in the data, but in our inadequate interpretations of them. It is tempting in research on reasoning and other cognitive processes to deal with either solution latency or error rate to the exclusion of the other. Few studies give serious consideration to both. Most often, the inattention to one or the other dependent variable is not justified; sometimes, it is justified by an author's pointing to the high correlation between latencies and errors across conditions. This justification is unacceptable. On the one hand, interpretation of solution latency by itself is inadequate, because the unexplained variance in error rate may be both statistically significant and of signal importance in obtaining a complete understanding of the problem-solving process. On the other hand, interpretation of error rate by itself is inadequate, because error rate may be a complex variable comprising two kinds of errors that can be disentangled and thereby separately understood only in the context of solution latency. The present work shows this complexity in error rates for linear syllogism problems, and previous work shows it in error rates for the only other kind of problem that has been similarly analyzed, analogies (Sternberg, 1977b). Understanding of cognitive processes seems to require that serious attention be paid to both latencies and errors.

Appendix

Observed and predicted latencies for the linear syllogisms are shown in Table A. A complete listing of the independent variables used in parameter estimation can be found in Table 2 of Sternberg (Note 1). The listing is available upon request. Parameter estimates used in computing predictions were as follows:

Mixed model: marking, 357 ± 64 msec; negation, 127 ± 70 msec; pivot search, 796 ± 168 msec; response search, 485 ± 111 msec; noncongruence, 437 ± 119 msec; encoding + response, 4600 msec. (These parameter estimates differ slightly from those presented in Table 2 because they are based upon only the 32 linear syllogisms, exclusive of the 8 two-term series problems.)

Linguistic model: marking, 357 ± 100 msec; negation, 326 ± 87 msec; noncongruence, 636 ± 173 msec; linguistic pivot search, 186 ± 200 msec; encoding + response, 4696 msec.

Spatial model: marking, 357 ± 100 msec; negation, 326 ± 86 msec; premise order, 5 ± 173 msec; spatial pivot search, 465 ± 122 msec; encoding + response, 4594 msec.

Insert Table A about here

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2. Schustack, M. W. Personal communication, August, 1977.

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Footnotes

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[1]The models were fit to geometric mean latencies for 32 data points. The quality of the data are suspect, however, because (a) there were only 13 subjects, with three observations per subject, (b) the longest latency for each subject for each item (33% of the observations) was discarded, (c) and error responses were also discarded (7% of the observations).

[2]Reliability of the latency data for the three-term series problems was computed by arbitrarily dividing the subjects into two halves, correlating the two sets of latencies across the 32 item types, and correcting the resulting correlation by the Spearman-Brown formula.

[3]Significance of the residual variance was determined by computing residuals of the observed from the predicted latencies for each of two arbitrarily chosen groups of subjects, correlating the residuals, and correcting the resulting correlation by the Spearman-Brown formula.

Table 1

Quantitative Fits of the Models to the Latency Data

Data Set	Item Latencies $\bar{X}$	$S_{\bar{X}}$	R^2 for Model Mixed	Linguistic	Spatial
3-Term Series					
All Adjectives	5922	128	.843**	.592**	.606**
Taller-Shorter	5824	138	.690**	.528**	.563**
Better-Worse	5964	139	.692**	.468**	.396**
Faster-Slower	5964	153	.683**	.586**	.576**
2- & 3-Term Series					
All Adjectives	5245	240	.966**	.921**	.924**

Note: Response latencies are presented in msec.

$^{**}p < .01$

Table 2

Latency Parameter Estimates for Present Experiment

and Two Previous Experiments:

Mixed Model

	Estimated Latency		
	Speed Emphasis	Accuracy Emphasis	
Latency Parameter	Present Experiment	Experiment 3[a]	Experiment 4[a]
Encoding	1354**	2986**	3124**
	(70)	(184)	(152)
Negation	143*	184*	244**
	(65)	(86)	(71)
Marking	327**	307**	380**
	(58)	(73)	(63)
Pivot Search	788**	1154**	1008**
	(159)	(226)	(174)
Response Search	485**	522**	656**
	(108)	(163)	(118)
Noncongruence	395**	538**	396**
	(102)	(119)	(111)
Response	1944	2517	2353

Note: Standard errors of parameter estimates are shown in parentheses below the appropriate estimates. All latencies are in msec.

[a]Data from Sternberg (Note 1)

*$p < .05$

**$p < .01$

Table 3

Quantitative Fits of the Models to the Error Data

Partitioned by Pseudo-Deadlines

Pseudo-Deadline (sec)	Proportion of Errors $\overline{X}$	$S_{\overline{X}}$	R^2 for Model Mixed	Linguistic	Spatial
2	.998	.001	.053	.031	.027
4	.779	.018	.774**	.487**	.419**
6	.432	.021	.722**	.576**	.476**
8	.222	.018	.804**	.652**	.687**
10	.131	.012	.454**	.498**	.417**
12	.098	.009	.440**	.428**	.417**
14	.080	.009	.395**	.446**	.405**
16	.076	.009	.334*	.407**	.339**
∞	.069	.008	.263	.387**	.276

Note: Model fits are for three-term series, all adjectives combined.

*$p < .05$

**$p < .01$

Table 4

Standardized Parameter Estimates for Error Data Partitioned by Pseudo-Deadlines and for Latency Data

Mixed Model

Pseudo-Deadline (sec)	Marking	Negation	Mixed Pivot Search	Noncon-gruence	Response Search
2	-.06	.20	-.16	-.06	.11
4	.40**	.16	.40**	.25**	.48**
6	.43**	.20	.29*	.32**	.44**
8	.52**	.03	.45**	.37**	.28**
10	.48**	.01	.23	.29**	.23
12	.41**	-.16	.33*	.29*	.23
14	.43**	-.19	.26	.30*	.17
16	.42**	-.20	.26	.23	.16
∞	.38*	-.15	.12	.23	.19
Latencies	.43**	.18*	.48**	.31**	.34**

Linguistic Model

Pseudo-Deadline (sec)	Marking	Negation	Linguistic Pivot Search	Noncon-gruence
2	-.06	.11	-.06	-.11
4	.40**	.39**	.19	.37**
6	.43**	.36**	.31**	.40**
8	.52**	.29**	.21*	.50**
10	.48**	.14	.36**	.35**
12	.41**	.03	.33*	.39**
14	.43**	-.03	.35*	.38**
16	.42**	-.05	.38**	.30*
∞	.38**	-.09	.41**	.26*
Latencies	.43**	.46**	.11	.44**

Table 4 Continued

Spatial Model

	Marking	Negation	Spatial Pivot Search	Premise Order
Pseudo-Deadline (sec)				
2	-.06	.11	.00	.11
4	.40**	.39**	.32*	-.06
6	.43**	.36**	.37**	.14
8	.52**	.29**	.57**	.00
10	.48**	.14	.41**	.04
12	.41**	.03	.48**	.10
14	.43**	-.03	.47**	.06
16	.42**	-.05	.39**	.09
∞	.38*	-.09	.33*	.11
Latencies	.43**	.46**	.46**	.00

Note: Model fits are for three-term series, all adjectives combined.

*p <.05
**p <.01

Table 5

Quantitative Fits of the Models to the Latency Data

Partitioned by Pseudo-Deadlines

Pseudo-Deadline (sec)	Item Latencies $\overline{X}$	$S_{\overline{X}}$	N^{a}	R^2 for Model Mixed	Linguistic	Spatial
	Latencies above Pseudo-Deadline					
2	5930	129	32	.846**	.607**	.606**
4	6680	98	32	.680**	.546**	.591**
6	8321	124	32	.452**	.339**	.435**
8	10414	160	32	.081	.066	.054
10	12912	508	30	.271	.122	.203
12	14937	584	25	.247	.225	.238
14	17740	592	13	.367	.280	.060
16	19122	538	10	.224	.400	.141
∞	-----	---	0	----	----	----
	Latencies below Pseudo-Deadline					
2	-----	---	0	----	----	----
4	3332	30	32	.454**	.356*	.377*
6	4356	46	32	.711**	.378*	.424**
8	5038	63	32	.747**	.488**	.400**
10	5434	91	32	.844**	.585**	.551**
12	5644	103	32	.824**	.643**	.577**
14	5776	112	32	.795**	.593**	.545**
16	5813	117	32	.793**	.597**	.555**
∞	5922	128	32	.843**	.592**	.606**

Table 5 Continued

Note: All latencies are expressed in msec. Modeling was of the 32 three-term series item types.

[a] $\underline{N}$ refers to number of item types (out of 32) for which there were any observations (nonmissing data) above or below pseudo-deadline.

$^{*}\underline{p} < .05$

$^{**}\underline{p} < .01$

Table 6

Quantitative Fits and Standardized Parameter Estimates of the Canonical Models to the Latency and Error Data

	Variate 1	Variate 2
Canonical R^2		
Mixed Model	.849**	.142
Linguistic Model	.632**	.268*
Spatial Model	.622**	.160
Standardized Parameter Estimates for Dependent Variables		
Mixed Model		
Latency	.96	----
Error Rate	.10	----
Linguistic Model		
Latency	.87	-.60
Error Rate	.29	1.02
Spatial Model		
Latency	.92	----
Error Rate	.20	----

Table 6 Continued

	Variate 1	Variate 2
Standardized Parameter Estimates for Independent Variables		
Mixed Model		
Marking	.49	---
Negation	.17	---
Pivot Search (Mixed)	.52	---
Noncongruence	.34	---
Response Search	.37	---
Linguistic Model		
Marking	.61	.24
Negation	.47	-.70
Pivot Search (Linguistic)	.27	.67
Noncongruence	.58	-.01
Spatial Model		
Marking	.60	---
Negation	.51	---
Pivot Search (Spatial)	.62	---
Premise Order	.03	

Note: All model fitting was done on the 32 three-term series item types.

*p <.05

**p <.01

Table 7

Quantitative Fit and Standardized Parameter Estimates of the Full Canonical Model to the Latency and Error Data

	Variate 1	Variate 2
Canonical R^2		
Full Model	.858**	.432*
Standardized Parameter Estimates for Dependent Variables		
Latency	.94	-.48
Error Rate	.15	1.05
Standardized Parameter Estimates for Independent Variables		
Marking	.50	.29
Negation	.20	.04
Mixed Pivot Search	.43	-.88
Response Search	.37	.05
Noncongruence	.25	-.10
Linguistic Pivot Search	.04	.86
Premise Order	.02	.17
Spatial Pivot Search	.17	.62

Note: All model fitting was done on the 32 three-term series item types.

*$p < .05$

**$p < .01$

Table 8

Correlations of Canonical Variate Scores with Original Variables

Original Variable	Variate 1		Variate 2	
	Dependent	Independent	Dependent	Independent
Dependent				
Latency	.99***	.92***	-.14	-.09
Error Rate	.45**	.42**	.89***	.59***
Independent				
Marking	.46**	.50**	.19	.29
Negation	.42**	.45**	-.31	-.47**
Mixed Pivot Search	.65***	.70***	-.23	-.34
Response Search	.35	.37*	.03	.05
Noncongruence	.46**	.49**	.06	.09
Linguistic Pivot Search	.17	.18	.37*	.57***
Premise Order	.02	.02	.11	.17
Spatial Pivot Search	.48**	.52**	.13	.19

*p <.05

**p <.01

***p <.001

Table A

Observed and Predicted Latencies for Linear Syllogisms

Item No.	Code[a]	Observed Latency	Predicted Latencies		
			Mixed Model	Linguistic Model	Spatial Model
1	00001	5223	5085	4882	5059
2	00100	5096	5394	5875	5416
3	00000	4630	4600	4696	5064
4	00101	5568	5878	5689	5421
5	11000	5481	5750	6232	5778
6	11101	6337	6155	5953	6135
7	11001	6159	6235	6046	5773
8	11100	5888	5670	5767	6130
9	01001	5184	5442	5053	4951
10	01100	4927	5313	5410	5308
11	10000	5581	4957	5053	4956
12	10101	5601	5798	5410	5313
13	10001	6296	5878	5689	5881
14	10100	5991	5750	6046	6238
15	01000	5234	5394	5689	5886
16	01101	6336	6235	6046	6243
17	11011	6860	6488	6698	6425
18	11110	5452	5923	6419	6782
19	11010	7219	6800	6884	6430
20	11111	7110	7204	6605	6787
21	00010	5080	4853	5348	5716
22	00111	5719	6132	6341	6073
23	00011	5835	6135	5534	5711
24	00110	6188	6443	6527	6068
25	10011	7406	6928	6341	6533
26	10110	6904	6800	6698	6890
27	01010	6308	6443	6341	6538
28	01111	7067	7285	6698	6895
29	01011	5635	5695	5705	5603

Table A Continued

Item No.	Code[a]	Observed Latency	Predicted Latencies		
			Mixed Model	Linguistic Model	Spatial Model
30	01110	5664	5267	6062	5960
31	10010	5222	5210	5705	5608
32	10111	6288	6051	6062	5965
RMSD			292	449	449

Note: All latencies are presented in msec.

[a]Five-digit code represents item type. For code abcde,

a--First premise adjective marked? (0=no, 1=yes)

b--Second premise adjective marked? (0=no, 1=yes)

c--Question adjective marked? (0=no, 1=yes)

d--Premises negated? (0=no, 1=yes)

e--Answer to problem in first premise? (0=no, 1=yes)

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